



IMPROVISED CNN BASED MODEL FOR CLASSIFYING THE STRESS LEVEL OF THE PLANTS

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Abstract: One of the major obstacles that an agriculturist may experience in their cultivation is plant stress, which can result in severe economic crop loss. Nitrogen deficiency is one of the most common causes of plant stress. Nitrogen deficiency causes stunted growth in plants, depending on the severity of the stress. To aid agriculturists, developers are investigating several approaches for measuring plant stress. To evaluate plant stress, the suggested system uses Deep Learning and convolutional neural networks, as described in this research. Deep learning-based methods are more efficient at measuring different plant traits for diverse genetic discoveries while searching for plant stress than traditional image-based phenotyping methodologies. This research takes a deep learning method to picture analysis. This suggested approach uses deep convolutional neural networks (CNNs) to detect as well as pixel-wise segment features to capture high-resolution photos without sacrificing pixel density, resulting in more accurate detection. In addition, the proposed model also outperforms traditional Machine Learning techniques like SVM, KNN, DT by achieving an average of 10% better accuracy.

Keywords: Deep learning; Convolutional neural network; Plant stress; Transfer learning;

LITERATURE SURVEY:

There was plenty of related work & research done in the form of literature survey to acquire the knowledge & skills needed to complete this project. This led us to come across various project work, thesis & technical papers accompanied by various reviews given on them. We will be discussing some of the papers & the work done in them & then reviewing by comparing them to our project work.

In [1], deep neural networks have achieved promising results in several fields. However, one of the main limitations of these methods is the need for large-scale datasets to properly generalize. (Tassis, L. M. et al. 2022)

In [2], Deep learning is a subset of machine learning and it is dedicated to the development of machines which would learn based on the given inputs and eventually attaining Artificial Intelligence inspired by the human brain. (Haripriya, P. et al. 2019)

In [3], Deep Convolutional Neural Network (CNN) is a special type of Neural Networks, which has shown exemplary performance on several competitions related to Computer Vision and Image Processing. (Khan, A. et al. 2020)

In [4], Plant Stress detection is a vital farming activity for enhanced productivity of crops and food security. (Kirongo, C., et al. 2019)

In [5], The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers and three fully-connected layers with a final 1000-way softmax. (Krizhevsky, A., et al. 2019)

In [6], The control of plant diseases is a major challenge to ensure global food security and sustainable agriculture. (Lee, S. et al. 2020)

In [7], Aiming at the problems that the traditional CNN has many parameters and a large proportion of fully connected parameters, an image classification method is proposed, which is based on improved AlexNet. (Li, S. et al. 2022)



In [8], Crop diseases are a major threat to food security, but their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure.. (Mohanty, S. et al. 2016)

In[9], Deep convolutional neural networks are an efficient model of autonomous feature extraction that has been shown to be fairly effective for detection and classification tasks.. (Saber Anari, M. 2022)

In[10], Deep learning(DL),a subset of machine learning approaches, has emerged as a versatile tool to assimilate large amounts of heterogeneous data and provide reliable predictions of complex and uncertain phenomena.. (Singh, A. K., et al 2018)

INTRODUCTION:

Agriculture forms the basis of food security and economic growth in most countries. However, in spite of the climatic conditions, most farmers often have to deal with different pests and diseases attacking their crops. In order to overcome this challenge, accurate and timely detection of the pests and diseases would likely lead to appropriate application of remedial measures. On the contrary, inaccurate and untimely detection of pests and disease in plants is a common problem in the agriculture industry among farmers. This not only raises agricultural production costs, but also causes significant losses, resulting in hunger and food scarcity. Plant stress caused by pests and/or diseases is the cause of crop failure.

Plant stress can be biotic or abiotic in nature. Biotic stress is caused by living organisms such as fungi, parasites, and bacteria, and can result in nutrient shortages. Abiotic stresses, on the other hand, are caused by non-living elements, most of which are related to the environment.

All of these pressures, by chance, reveal themselves primarily in the plant's outward appearance. As a result, distinguishing between the many forms of plant stress and associated stress can be difficult. A lot of these stresses can also cause similar symptoms in plants. A better understanding of the picture characteristics of the various plant stresses is required to solve this problem.

Nutrient induced stress in plants is the most critical factor and can significantly reduce the agricultural yield. Nutrient induced stress can result from either low level or excess level of minerals in the plant system. With 'improved CNN based model for classifying the stress level of plants using a deep learning approach' we can measure the nitrogen availability which gives three samples. Nitrogen deficiency affects certain visible plant traits such as area, color, the number of leaves and plant height, etc. Most traditional phenotyping techniques are destructive and time-consuming with intensive labor requirements, and hence, smart auto-mated plant phenotyping techniques that can help identify the stress level in less time without disturbing the plant are needed. With the recent advances in computer vision and object recognition, it has become quite straightforward to capture high resolution images in both the visible as well as the infrared spectrum.

MATERIALS AND METHOD:

This section provides an overview of the dataset and methods used to determine the level of nitrogen stress in plants using the datasets. It first describes the dataset used in the experiment before moving on to the deep learning approach with CNN.

Dataset Description

A total of 65,760 leaf photos were used in this work, which were separated into 9 class labels assigned to them, with 59,184 being used for training and 6,576 being used for validation. We also calculated accuracy for 10,800 leaf images where 10,800 plant leaf images were compressed of 65,760 plant leaf images, with 10,000 being used for training and 800 being used for validation.

Deep Learning

The potential and prospects of using machine learning for high throughput stress phenotyping in plants were recently reported. The plant science community is facing a data deluge of plant photos under varied conditions and pressures, thanks to fast rising sophistication and capabilities (Biotic and Abiotic). This increased interest in automated ways to extract physiologically relevant features from big datasets with the goal of identifying and measuring plant stressors has resulted from the capacity to undertake high throughput phenotyping. Many computer vision problems have been solved using deep learning approaches based on ANNs. Traditional ML and CNN are fundamentally different in that CNN does not require handcrafted features. CNN's can extract features directly from raw images by tuning the parameters in the convolutional and the pooling layers.



Proposed convolutional neural network (CNN)

The architecture of the proposed model is structured as (conv8-bn-relu), max-pool, (conv16-bn-relu), max-pool, (conv32-bn-relu), max-pool, (conv64-bn-relu), max-pool, (conv128-bn-relu), fully connected, soft-max, and classification output layer. The conv(n) represents a 2d convolution layer with kernel size as 3x3 and stride 1.

Implementation of deep convolutional neural network model:

The Deep Convolutional Neural Network (DCNN) Model was developed using the TensorFlow deep learning platform for the construction of the digital image model for plant stress detection. TensorFlow is used to compute numerically mathematical graphical data. The graphs' edges are made up of tensors, which are multidimensional data arrays that communicate between nodes. With a single Application Process Interface, TensorFlow's architecture is later deployed to either Central or Graphical Processing Units on a smartphone device, server, or desktop (API). TensorFlow was first created by the Google research team for machine learning and deep neural network research. We create a model for a deep convolutional neural network on the TensorFlow platform and test it using the SoftMax activation function in the output layer to provide a range of probabilities to the various output options in this study.

Structure of the CNN:

Neurons and Layers are key in the modeling of neural network structures. For CNN the number of input and output neurons is predetermined based on the dimension of the training set and the prediction sets. The structure of the CNN model used in this study is given in Figure below

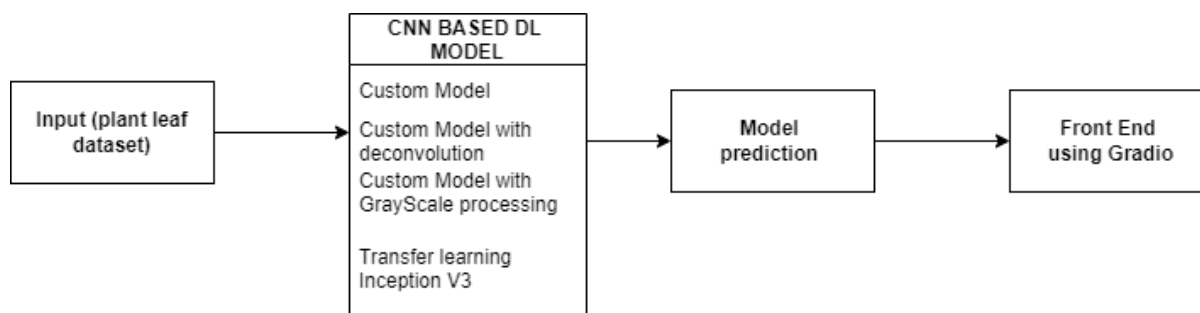


Figure 1. Deep learning Proposed CNN Architecture

IMPLEMENTATION

TensorFlow is an open-source end-to-end framework for building Machine Learning apps. It's a symbolic math toolkit that performs a variety of tasks including deep neural network training and inference using dataflow and differentiable programming. It enables programmers to construct machine learning applications by utilizing a variety of tools, frameworks, and community resources.

Google's TensorFlow is now the most well-known deep learning package on the planet. Machine learning is used by Google in all of its products to enhance search, translation, picture captions, and recommendations.

RESULTS AND DISCUSSION

In this Section, we have used multiple models to Evaluate and compare the performance of Proposed System, where all models use Adam as Optimizer and (Keras.Sequential) as standard Model. Before providing the dataset as input, Image size is reduced to 224 x 224.

Various Models used in this paper and their results are as followed:

Model 1: Base Model

This Model is used for 2 data-set of plant-leaf images. Architecture of Base model is structured as (Conv2D-8-3*3-relu), max-pool, (Conv2D-16-3*3-relu), max-pool, (Conv2D-32-3*3-relu), max-pool, fully connected, soft-max, and Classification output layer

Data-set : 65,760 images

Using this data-set Base Model provides Training Accuracy of 79% and Validation Accuracy of 77% using 10 epochs. Following fig 2 shows the graph for Accuracy and loss.

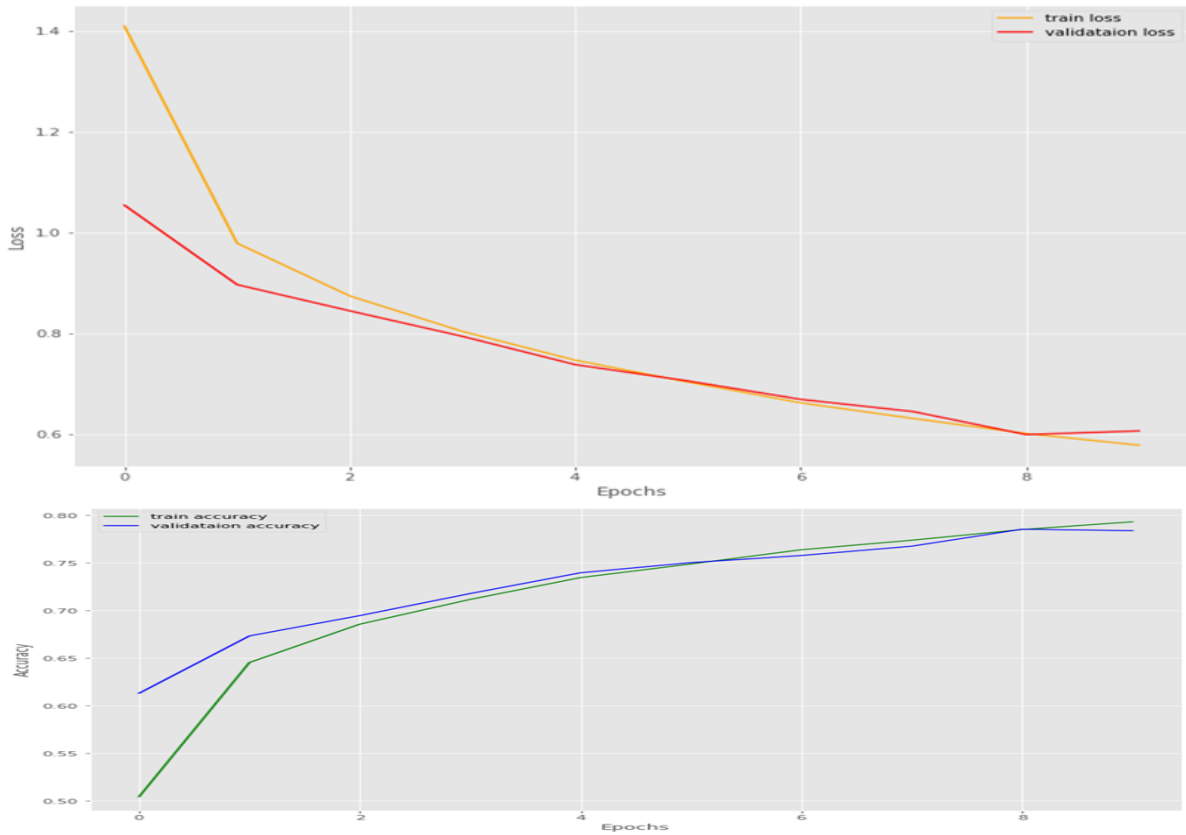


Fig 2 Accuracy and loss for data-set 65,670

Data-set : 10,800 images (Compressed dataset of 65.760 images)

Using this data-set Base Model provides Training Accuracy of 71% and Validation Accuracy of 68% using 10 epochs. Following fig 3 shows the graph for Accuracy and loss

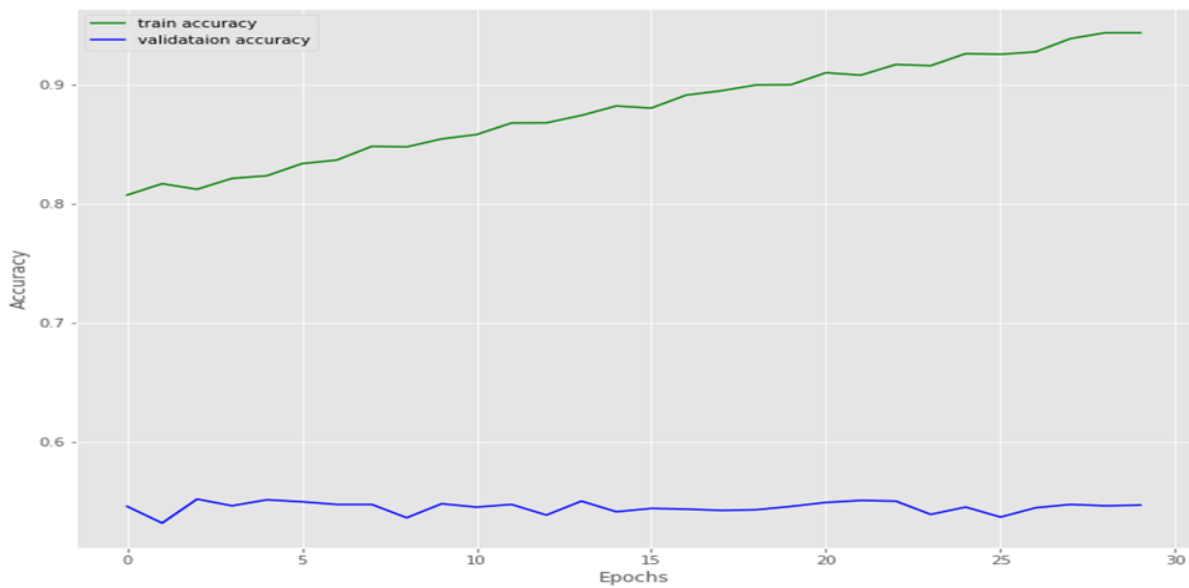


Fig 3 Accuracy and Loss for dataset of 10,800



Model 2: Base Model + Gray-scale Image Processing

This Model is used for data-set of 10,800 images (compressed of 65,760 images) of plant-leaf. This Model uses Gray-Scale image pre-processing code to convert the entire data-set into gray-scale images and same is given as input to the Base Model. Model 2 provides the Training Accuracy of 94% and Validation Accuracy of 54% using 30 epochs . Following fig 4 show the graph for accuracy and loss.

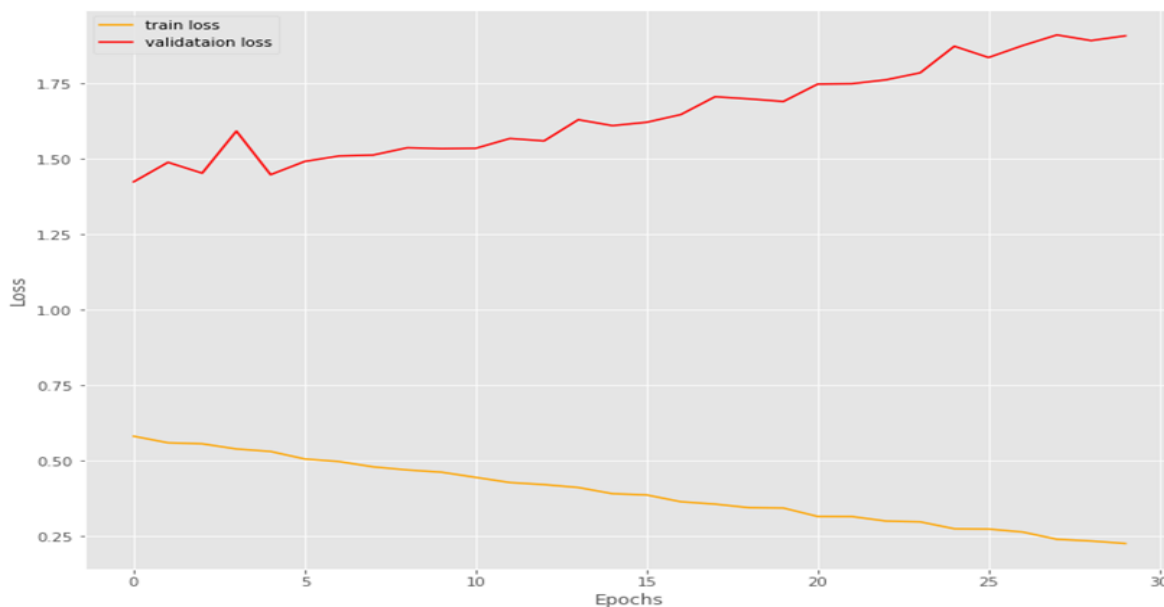


Fig 4 Accuracy and Loss for Dataset 10,800

REFERENCES:

- [1] Tassis, L. M., & Krohling, R. A. (2022). Few-shot learning for biotic stress classification of coffee leaves. *Artificial Intelligence in Agriculture*, 6, 55–67. <https://doi.org/10.1016/j.aiaa.2022.04.001>
- [2] HariPriya, P., Porkodi, R., (2019). Deep Learning Pre-Trained Architecture Of Alex Net And Googlenet For DICOM Image Classification. *INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH*, 8(11). www.ijstr.org
- [3] Khan, A., Sohail, A., Zahoor, U., & Qureshi, A. S. (2020). A survey of the recent architectures of deep convolutional neural networks. *Artificial Intelligence Review*, 53(8), 5455–5516. <https://doi.org/10.1007/s10462-020-09825-6>
- [4] Kirongo, C., Omieno, K., Mutua, M., & Ogemah, V. (2019). Plant Stress Detection Accuracy Using Deep Convolution Neural Networks. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 263–270. <https://doi.org/10.32628/cseit195447>
- [5] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (n.d.). ImageNet Classification with Deep Convolutional Neural Networks. <http://code.google.com/p/cuda-convnet/>
- [6] Lee, S. H., Goëau, H., Bonnet, P., & Joly, A. (2020). New perspectives on plant disease characterization based on deep learning. *Computers and Electronics in Agriculture*, 170. <https://doi.org/10.1016/j.compag.2020.105220>
- [7] Li, S., Wang, L., Li, J., & Yao, Y. (2021). Image Classification Algorithm Based on Improved AlexNet. *Journal of Physics: Conference Series*, 1813(1). <https://doi.org/10.1088/1742-6596/1813/1/012051>
- [8] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7(September). <https://doi.org/10.3389/fpls.2016.01419>
- [9] Saberi Anari, M. (2022). A Hybrid Model for Leaf Diseases Classification Based on the Modified Deep Transfer Learning and Ensemble Approach for Agricultural AIoT-Based Monitoring. *Computational Intelligence and Neuroscience*, 2022, 1–15. <https://doi.org/10.1155/2022/6504616>
- [10] Singh, A. K., Ganapathysubramanian, B., Sarkar, S., & Singh, A. (2018). Deep Learning for Plant Stress Phenotyping: Trends and Future Perspectives. In *Trends in Plant Science* (Vol. 23, Issue 10, pp. 883–898). Elsevier Ltd. <https://doi.org/10.1016/j.tplants.2018.07.004>